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Degradation based optimization framework for long term applications of energy systems, case study: Solid oxide fuel cell stacks

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ABSTRACT

Depletion of fossil fuels has increased the pressure on energy systems to operate in the most efficient and economical mode. This tendency promotes energy systems to operate at optimum operating conditions, which maximizes the system profit over lifetime. Recently, there have been many attempts to maximize lifetime profit. Most of them concentrate on the power generation aspect without incorporating further aspects such as system degradation and profitability through lifetime. However, the main intention of the system operators is to optimize the profitability of system at the moment of operation and not the total profitability through the system lifetime. In this study a novel approach is developed which considers degradation mechanisms in optimization procedure. A DBO (degradation based optimization) framework maximizes system profit through its lifetime. The proposed framework can be applied to energy systems and the optimum operating conditions and replacement intervals can be determined. Solid oxide fuel cell is considered as the case study to validate the developed framework. The results show the value and effectiveness of DBO framework to improve the lifetime profit during system operation. Using DBO, the system lifetime profit for proposed case study is increased up to 10.45%.

1. Introduction

The major proportion of performance deterioration of energy systems result from a gradual and irreversible accumulation of damage that occurs during a system's life cycle. This process is known as degradation [1]. Degradation models attempts to characterize the evolution of degradation mechanisms [2].

DBO (Degradation based optimization) is an optimization model that considers systems degradation mechanisms in the optimization procedure. The goal of DBO is defining the optimum operating condition or design parameters of the system to maximize or minimize a specific objective function. In energy systems, mostly the optimum operating conditions lead to the minimum system total cost or maximum system profit through its operation lifetime. DBO framework consists of degradation and process modules which are added to an optimization module. Degradation and process modules, determine performance deterioration as a function of system operating conditions. Furthermore, optimization module includes an objective function as well as technical and economic constraints.

Based on the reviewed literature, the approximation of system degradation is a well-developed field and a large stream of research in energy systems area focused on component [3] and system degradation models [4] with various purposes. For instance, Guenther et al. [5] developed degradation model for batteries. Similarly, optimization of operating conditions according to plant fuel consumption or power demand regardless degradation process in power systems [6] or other energy conversion systems [7] are also available. Baldick [8] scheduled generator start-ups, shut-downs, and generation levels to minimize production and start-up/shut-down costs. In another study, Green [9] studied traditional models of optimal electricity pricing. In such studies optimization is done regardless system component degradation.

However, there are a few studies which optimize energy system based on degradation mechanisms. In this field, Wu et al. [10] developed an optimization model to minimize the total cost of degradation based maintenance by determining an optimal interval of condition monitoring. Moreover, Song et al. [11] presented a model to simultaneously minimize the total cost of the system and the capacity loss of battery over a typical China Bus Driving Cycle. In the optimization procedure, battery degradation model is

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Nomenclature

AV	Asset value
c	Cost
dr	Degradation rate
e	System output
F	Fuel consumption
i	Current density
J	Profit
LT	Degradation level of component
$\dot{m}$	Mass flow rate
p	Price
q	Income
u	System decision variables
V	Voltage
w	Weighting factor
x	System state variables
y	System performance index
z	Continuous variables
θ	Degraded surface
ε	Random error
λ	Random effect parameter
ω	Fixed effect parameter

Subscript and super script

0	Initial time
d	Degradation
f	Fuel
k	System outputs (heat, electricity)
l	Lifetime
m	Number of observations/tests
max	Maximum value
min	Minimum value
n	Number of components
NG	Natural gas
o	Operation

considered. Song et al. [12] developed another optimization model based on developed battery degradation model which optimizes components sizes and the system control strategy simultaneously.

In above literature, the aim of the optimization, decision variables and degradation modeling methodology are different. Mostly the objective of the optimization is maximizing energy production or minimizing system cost and decision variables are design or operating parameters. Moreover, degradation modeling methodology is data-driven or principle based. For instance, Wen et al. [13] developed a data-driven optimization model for SOFC (solid oxide fuel cell). In optimization model, the objective is maximizing generated electricity and decision variables are geometric and operating parameters. Moreover, modeling is based on system historical data and the individual data-driven degradation model is developed. The characteristic of other related researches in this area are presented in Table 1.

In recent years, degradation based optimization models consider degradation cost as a specific term in the objective function. Johnston et al. [20] consider the cost of storage degradation due to ageing effects related to cycling of charge. Fares et al. [21] introduced degradation cost in objective function which is equal to revenue reduction due to power generation deterioration.

It should be noted that the storage systems are dominant equipments in degradation analysis. In related studies the battery degradation cost is added to the system total costs. The differences are in the objective function of optimization and battery degradation models for different storage systems such as residential [22] or transportation applications [23]. In research performed by Atia et al. [24] the objective function is the minimization of the annualized cost of system. The battery degradation factor is derived as a function of temperature, SOC (State of charge) and SOC swing effect based on experimental data. Kam et al. [25] developed linear optimization model that maximize self-consumption of PV (photovoltaic) power. To give an indication of the control algorithms impact on battery lifetime they use three indicators: energy throughput, rate of charge and discharge and SOC. Song et al. [26], optimized the size of energy storage system in vehicles based on dynamic degradation model of the battery. The operation costs of different hybrid energy storage system, including the electricity and the battery degradation costs over a whole driving cycle are minimized in the optimization process. Results showed that about 50% of the operation cost of the energy storage system can be reduced.

Obviously, in energy systems there are not much literature which considers degradation cost in the objective function. Moreover, beside energy system cost, lifetime profit is another key component which must be considered in optimization of operating condition. In this work, an optimization framework is developed with the aim of maximizing lifetime profit based on degradation mechanisms. The objective of this study is to present the optimal operating conditions and replacement intervals of an energy conversion plant over a long-term horizon that maximizes lifetime profit. In this regard, the DBO framework is developed. The key components resulting from the model are the fuel cost, system degradation cost and system income. This framework is applied to a SOFC power plant as a case study and optimum operating conditions and replacement intervals are derived.

This paper is organized as follows: Section 1 presented the evolution of DBO and its literature review. In Section 2, DBO concept and its importance are introduced. The proposed DBO framework is presented in three main modules. A brief discussion

Table 1
Literature survey of degradation based optimization models.

Authors	System	Purpose	Decision variables	Methodology
Gallestey et al., 2002 [14]	Gas turbine	Minimize system cost	Production scheduling	Data-driven model
Zaidan et al., 2015 [15]	Gas turbine	Increase the fidelity of failure-time	Prediction performance, computational speed	Data-driven model
Trecate et al., 2002 [16]	Steam and gas turbine	Minimize system cost	Steam mass flow, gas turbine load	Data-driven model
Uson et al., 2010 [17]	Power plant equipment	Different targets regarding degradation	Operating conditions	Principle based and data-driven model
Rasmekomen et al., 2013 [18]	Framework development	Minimize system cost	Maintenance interval	Data-driven model
Kima et al., 2014 [19]	PEM	Maximize mean voltage	Temperature	Data-driven model

followed by a review on modeling of energy conversion systems is presented for each module. Section 3 presents solution approach of DBO framework based on Genetic algorithm. Section 4 discusses how to apply the DBO framework on SOFC system as a case study. In this section flow diagrams and governing equations are presented for SOFC system. Results are presented in Section 5 and finally the study concludes with an overall discussion on the advantage of DBO framework in Section 6.

2. DBO concept

Scheduling the operating conditions and replacement intervals over the system lifetime is a great issue. Variation of operating conditions and replacement intervals affect equipment degradation rate and reducing system profit [27]. This means that the trend of profit deterioration depends on system operating schedule. DBO (Degradation based optimization) is an optimization framework which optimizes operating condition and replacement intervals of energy system to achieve maximum profit through system operation lifetime. This framework addresses the effect of a given operating mode on the aging process of the energy system and includes aging parameters in the economic optimization [16]. DBO framework consists of three main modules which are solved simultaneously. To this aim, firstly system operation is modeled (process module) regardless degradation mechanism. This module describes how fuel is converted into system output. Secondly, degradation mechanisms are modeled (degradation module). By integrating these two modules, system performance deterioration is defined. Finally by applying optimization module the optimal operating conditions and replacement intervals are derived.

The framework flow diagram of the DBO modules is presented in Fig. 1. As it can be seen, design and operating parameters affect DBO framework. Based on the system under study, DBO decision variables can be either design parameters, operation parameters or both.

2.1. Process module

Process module describes how fuel is converted into electrical and thermal energy. This module gives the system performance as a function of system operating and design parameters. System performance can be evaluated using various indexes such as output power, output heat flux, and system efficiency. The general form of process module is as follow.

$$y = f(x, u, \delta, z) \tag{1}$$

$$g(u, x, \delta, z) \le h(u, x, \delta, z) \tag{2}$$

$$Z = \delta \cdot x \tag{3}$$

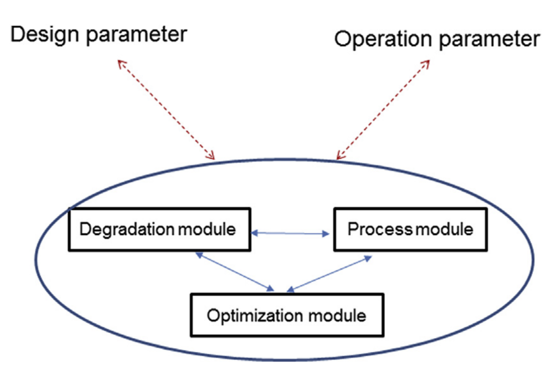

Fig. 1. DBO framework flow diagram.

Logical constraints (4)

The first equation is a set of linear or nonlinear equations, which shows the dependence of system performance index (y) to system state variables (x) and system decision variables (u).$\delta(t)$ and $z(t)$ represent auxiliary binary and continuous variables, respectively. In Eq. (2) system inequality constraints are presented. Eq. (3) defines binary variables which depend on system state. The binary variables are used in system modeling and constraints and show the existence and inexistence of equations based on system condition. The last equation (Eq. (4)) shows the system logical constraints [16,28]. It is worthy to indicate that if the operating condition of the system remains constant, the process model gives the constant profit through system lifetime.

2.2. Degradation module

Most failures of engineering systems result from degradation process [29]. Degradation module is used to compute component degradation through system lifetime at different operating conditions. For the purpose of lifecycle or ageing modeling two issues are critical in degradation models. Firstly, the model must provide a direct relationship between equipment load and equipment ageing. Ageing in a gas turbine, for example, takes into account effects like firing temperature, fuel type, fuel switch-over, use of power augmentation, trips, startups, etc. Secondly, the model must capture the equipment's operating history.

Models for degradation are generally either data-driven or derived from physical principles. Although the data-driven model is more commonly applied to analyze degradation data, viewing degradation through Physical principle-based model helps researchers theoretically characterize the failure process and predicting system behavior [30,2]. A comparison between the applicability of the data-driven and the principle based approaches is shown graphically in Fig. 2.

As it can be seen in Fig. 2, data-driven models are less reliable in comparison with principle based models because of two main reasons: firstly, data-driven models required historical system data to determine correlations, establish patterns, and evaluate data trends leading to failure. In many cases, there will be insufficient historical or operational data to obtain health estimates and determine trend thresholds for failure prognostics. Furthermore, in some situations, such as in stored, standby, non-operating modes or when failures are infrequent, the lack of sufficient data leads data-driven models to be less reliable [31]. Secondly, data driven models should be trained by the procedures which involve many uncertainties which leads them to be less reliable in comparison with principle-based models [32].

However, the principle-based model derives a mathematical model to describe unit performance. This model can take into

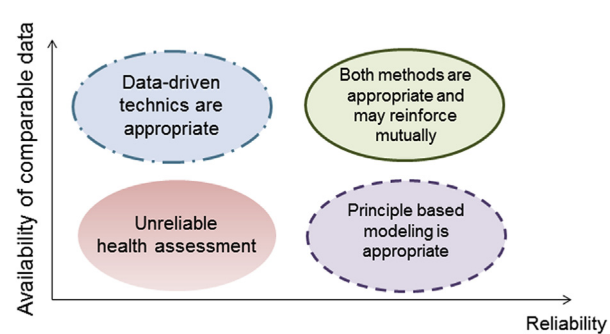

Fig. 2. Comparison between data driven and principle based degradation models [31].

account degradation caused by environmental conditions such as thermal loads, humidity, vibrations, and shock. Therefore, they can be used to estimate damage in situations where systems are in a non-operating state such as during storage and transportation.

2.2.1. Data driven model

Data driven model is used to determine the relationship between a system's inputs and outputs using a training data set that is representative of all the behavior found in the system [32] (see Fig. 3).

Most degradation data driven model of a system formulated as follow.

$$dr_{ij}(t) = \omega(t) + \lambda t_j(t) + \varepsilon_{ij}(t) = f(y, \dot{x}, x, u, t) \quad for \;\; i = 1, 2, .., n, j = 1, 2, ..., m \tag{5}$$

Where $dr_{ij}(t)$ is the degradation level of component i in the system at time t_j, $\omega(t)$ is a fixed effect parameter, λ is a random effect parameter which is assumed to have an exponential distribution and $\varepsilon_{ij}(t)$ is the random error term which is assumed to be independent and identically distributed with zero mean and constant variance. This model assumes $\varepsilon_{ij}(t)$ and λ are independent [30]. In Eq. (5), i,j varies as $i = 1, 2, 3, ..., n$ and $j = 1, 2, 3, ..., m$, respectively. Where n is the number of tested devices and m is the number of observations measured for each device. This method of regression is used in most experimental studies [33,34].

2.2.2. Physical principle-based model

Degradation is a continuous progression of undesirable mechanical, chemical and electrochemical mechanisms. In many experiments, these mechanisms are known. Based on the mechanical, chemical and electrochemical principle of the degradation mechanisms, each mechanism will be modeled. Finally by solving a set of equations, component degradation model will be as follow [2].

$$dr_i(t) = \frac{dLT_i(t)}{dt} = f(y, \dot{x}, x, u, t) \quad for \;\; i = 1, 2, ..., n \tag{6}$$

$dr_i(t)$ describes the degradation rate of component i. $LT_i(t)$ is the degradation level of component i at time t. This equation is a set of equations which shows the dependence of degradation rate to system state and decision variables.

2.3. Optimization module

Optimization module identifies an optimization procedure regarding ageing function. Therefore, by applying optimization module to the developed process and degradation modules, decision variables will be derived. The objective function of optimization module is maximizing profit through system operation lifetime, which is formulated as follow (Eq. (7)).

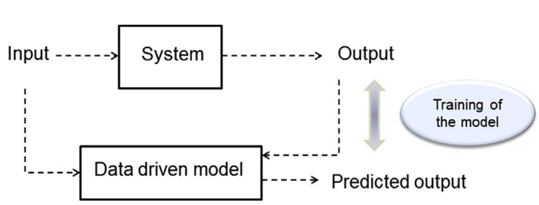

Fig. 3. Data driven degradation model flow diagram.

$$\max J[u(t), x(t), t_l] = \int_t^{t+t_l} (q(t) - c_o(t) - c_d(t))d\tau \tag{7}$$

The objective function depends on system decision variables, state variables and system operating lifetime t_l. The integration is over time and the integration interval t_l is the system operating lifetime. In the optimization objective function, the total profit of the system through its lifetime will be maximized. In Eq. (7), q is income including selling heat or/and electricity generation. c_o is system fuel cost (eg. natural gas). Finally, c_d is the degradation cost of system which determines system lifetime ageing (usage) cost.

2.3.1. Income

In this study, system income is the amount of energy production multiply by the unit price of the energy in a given period of time.

$$q(t) = \sum_i e_i(t) \times p_i \quad for \;\; i = 1, 2, .., k \tag{8}$$

e_i is the system output. Based on the system goal, it can be electricity or heat. p_i is the unit price of energy.

2.3.2. Fuel cost

Here, the fuel cost is the cost of utilized fuel during system operation lifetime. In the following equation, c_o is the fuel cost, c_f is the unit cost of fuel and F is the fuel consumption over desired period of time.

$$c_o(t) = F(t) \times c_f \tag{9}$$

2.3.3. Degradation cost

In most studies, maintenance and replacement costs are constant value and are applied to the system costs after a period of operation. However, degradation cost is the cost of system depreciation which leads system to fail or be maintained [14,16]. Degradation cost applies to system through time. The integration of degradation cost over time on a specific interval is equal to maintenance/replacement cost of equipment. Considering degradation cost differs from considering maintenance/replacement cost in two ways. Firstly, by considering degradation cost, system online (hourly) actual operating cost can be calculated. In addition, degradation cost, is based on system degradation. Therefore, operating conditions may affect system degradation cost. In other words, operating conditions alter the system online (hourly) actual operating cost.

System degradation cost is presented in the Eq. (10) which shows the asset value depreciation or lifetime usage cost due to a given operating strategy [14].

$$c_d(t) = \sum_{i=1}^{n} AV_i dr_i(t) \tag{10}$$

AV_i is the value of component i and $dr_i(t)$ denotes system component degradation rate, which is derived from degradation model [16]. As it can be seen, degradation cost is a linear function of system degradation rate.

Moreover, it is easy to see that the term $\int_t^{t+T} c_d d\tau$, in the objective function, is equal to the decrease in asset value during the time interval [t, t + T], thus this term helps to determine the more practical operational cost of a system [14].

3. Solution approach

In DBO (degradation based optimization), the system characteristic depends on time which necessitates using dynamic optimization methodologies. Therefore DBO is based on a dynamic optimization model framework [35] which is presented in the Fig. 4. Generally, the formulated problem consists of an optimization strategy, equality constraints vector, inequality constraints vector, variable constraints and the initial conditions [36].

Model equations are a set of partial differential equations which are derived from process and degradation modules. These equations are a function of state variables, decision variables and time as presented in Eq. (11).

$$g(\dot{x}, x, u, t) = 0 \tag{11}$$

In addition, model restrictions are the inequalities which show the system limits, operating conditions range and so on that can be modeled as (Eq. (12)–(14)).

$$h(\dot{x}, x, u, t) \geq 0 \tag{12}$$

$$x_{\min} \leq x(t) \leq x_{\max} \tag{13}$$

$$u_{\min} \leq u(t) \leq u_{\max} \tag{14}$$

Where $x(t)$ is the vector of state variables and $u(t)$ is the vector of decision variables. Dynamic optimization framework has given initial conditions as well.

$$x(t_0) = x_0 \tag{15}$$

As mentioned, the optimization problem finds optimal decision variables, which maximize the objective function in general form as follow.

$$\max J[u(t), x(t), t_l] \tag{16}$$

t_l is the given operating lifetime of the system. Optimization model determines the best replacement intervals and optimum operating conditions of the system to achieve the maximum profit during this operation lifetime. At system replacement time, system will be replaced with a new one. Therefore, in the modeling, state variables will be updated to their initial values at each replacement time. Solution approach of DBO is presented in the Fig. 5. At the initial time, operating and design parameters are known. In degradation module (based on operating conditions) the degradation mechanisms are modeled. Degradation mechanisms caused by physical, chemical and electrochemical reactions. These mechanisms, degrades design parameters of components such as length of TPB (triple phase boundaries), electrolyte conductivity and so on. Design parameters ageing are a function of the rate of physical, chemical or electrochemical reactions which are modeled in degradation module. Based on the values of degraded design parameters, process module calculates the system performance indexes (system efficiency or output power). Up to this stage, system performance as a function of operating condition can be evaluated. By using this function in the optimization module, optimum decision variables (operating conditions and replacement intervals) will be derived. The process continues till the proper convergence criteria are reached.

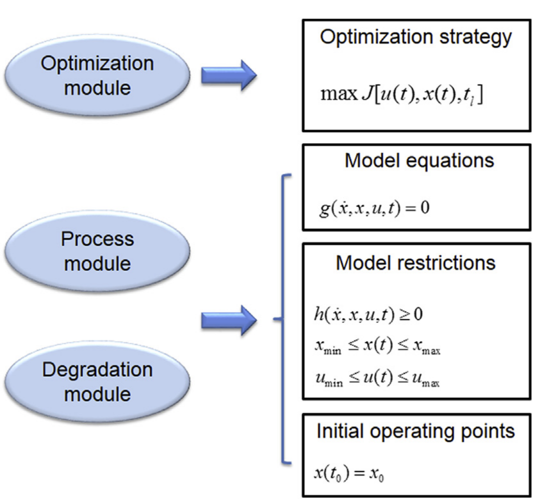

Fig. 4. DBO framework structure.

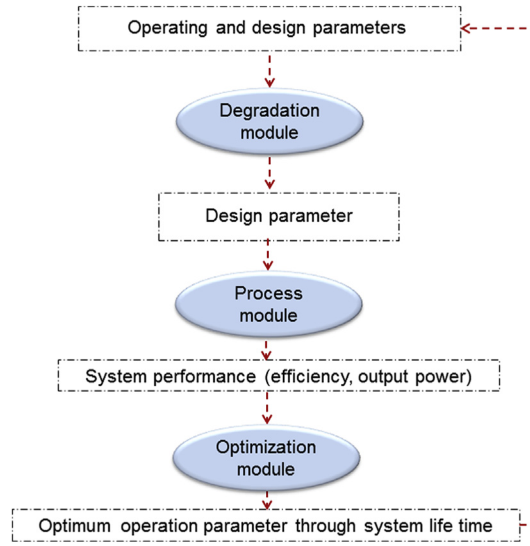

Fig. 5. Data flow diagram of DBO framework.

4. Case study

The proposed methodology is applied to evaluate the presented framework on a SOFC system which is widely recognized as the promising candidates for future energy conversion plant. Fig. 6 shows the schematic of an SOFC stack and major degradation mechanisms including chrome poisoning, Sulphur poisoning and Ni coarsening.

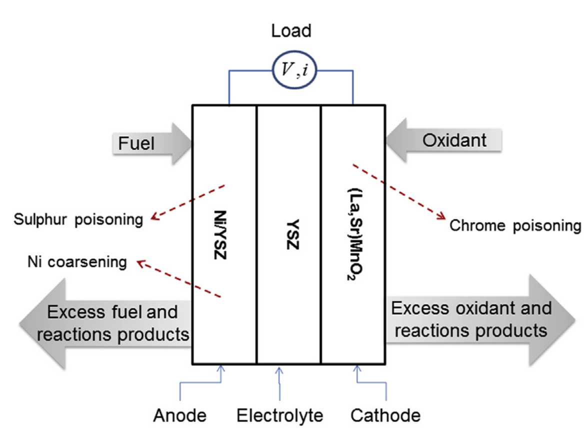

Fig. 6. Schematic and degradation mechanisms of SOFC.

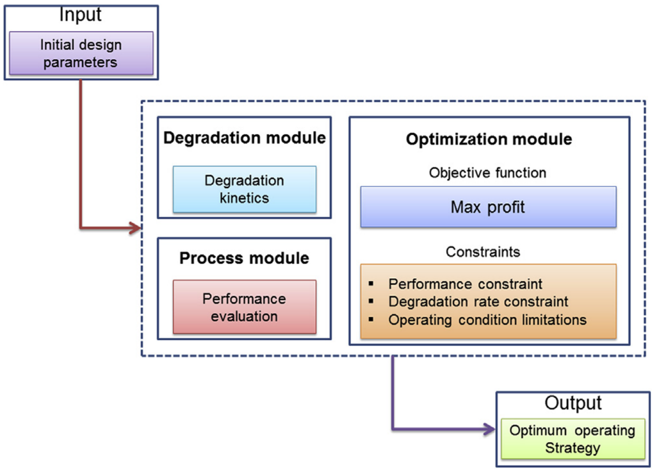

Fig. 7. DBO solution methodology.

In this study a 150 kW anode supported-SOFC is considered as a case study. In anode-supported stacks the major degradation mechanism is Ni coarsening which is considered in the developed optimization model. DBO (Degradation based optimization) solution methodology is presented in Fig. 7.

Based on the Fig. 7, inputs are SOFC initial design parameters which are categorized to degradable and non-degradable parameters. The non-degradable parameters are constant through system lifetime, but degradable parameters will be degraded because of degradation mechanisms. This inputs applied to the DBO framework. Process and degradation modules are developed based on the principles of SOFC operation and degradation mechanism. Moreover, optimization module finds the operating conditions and replacement intervals which maximize system profit through operation lifetime. The optimization objective is to maximize lifetime profit of the system regarding degradation mechanisms. The considered decision variables are fuel cell temperature and current density.

The terms of objective function (Eq. (7)) are presented as Eq. (17)–(19). c_o is the fuel cost (natural gas) and $\dot{m}_{NG}$ is fuel mass flow rate.

$$c_o(t) = \dot{m}_{NG}(t) \times c_f \tag{17}$$

q is the income of selling electricity and can be calculated using Eq. (18).

$$q(t) = V(t) \times i(t) \times p_1 \tag{18}$$

p_1 is the unit price of electricity. It should be noted in Eq. (18), system voltage $V(t)$ and current density $i(t)$ are degraded over time because of degradation mechanisms. The last term of objective function is degradation cost (c_d). This term is formulated as follow.

$$c_d(t) = \frac{d\theta(t)}{dt} \times AV_{SOFC} \tag{19}$$

θ is the degraded surface fraction of anode which is derived from degradation module. AV_{SOFC} is the cost of SOFC replacement.

The optimization model is also subject to several constraints. Performance and degradation constraints are derived based on process and degradation modules. In addition, it is assumed that SOFC fuel cell is designed to work in a specific temperature and current density rang. The proposed control variable constraints are expressed in Eq. (20)–(23).

$$u_{\min} \le u(t) \le u_{\max} \tag{20}$$

$$u(t) = [T, i] \tag{21}$$

$$u_{\min} = \left[T^{\min}, i^{\min}\right] \tag{22}$$

$$u_{\max} = \left[T^{\max}, i^{\max}\right] \tag{23}$$

There is no restriction for system state variables. Furthermore, the initial condition of state variable is as follow Eq. (24)–(26).

$$x(t_0) = x_0 \tag{24}$$

$$x(t) = [\theta(t)] \tag{25}$$

$$x_0 = \left[\theta^0\right] \tag{26}$$

$\theta(t)$ is the degraded surface area, which is equal to zero at the initial time of system operation. In addition, the given operating lifetime of the system is equal to 15 years. It is assumed that SOFC stack will fail if the half of the Nickel on the anode surface is oxidized. Optimization model determines the best replacement intervals and optimum operating conditions of SOFC stack to achieve the maximum profit during this operation lifetime. At system replacement time, stack will be replaced with a new one. Therefore, in the modeling, state variables will be updated to their initial values at each replacement time. For instance, the oxidized surface area will be equal to zero again.

5. Results and discussion

The SOFC process and degradation models are a set of partial differential equations which are solved based on proposed solution algorithm. In an effort to validate the process model, comparison of the model output with results published by Wen et al. [13] is performed. Based on results, at the same SOFC geometric dimensions and operating condition (1073 K), the general shape of two polarization curves are similar. The biggest difference observed is in the low and high current densities, which is under 5%. Furthermore, voltage degradation rate at different current densities is used to validate the degradation module of SOFC. Muller et al. [37] gathered experimental data at 1223 K Table 2 presents model output which are verified with experimental data at the first 500 h of system operation.

As it can be seen, the model prediction is in good agreement with the experimental data. At higher current densities, model indicates lower voltage degradation. Actually, at higher current densities, other degradation mechanisms occur in the anode supported stack, which are not considered in this study. However, the modeling results are nearly close to the experimental data in this range as well. Improvements in the agreement between the simulations and experimental data can be obtained by modeling all

Table 2
Comparison between experimental data and modeling results.

Current density (A/cm^2)	Fuel utilization %	Anode voltage degradation rate (V/1000hr)	
		Experimental data	Modeling results
0.2	83	0.032	0.039
0.52	38	0.057	0.047

degradation mechanisms. However, the main objective of the present study is to capture degradation profile over time which can be achieved with enough accuracy.

SOFC optimization model includes objective function, equal constraints which are derived from process and degradation model and unequal constraints which show system operation limits. Genetic algorithm is used to solve the optimization problem. The solution method of optimization is applied on the optimization case of Wen et al. [13] to maximize the power density at system initial operating time. Based on the developed methodology, the same results are derived.

To study the advantages of DBO framework, two optimization strategies are compared. At the first strategy, system operating conditions and replacement intervals will be optimized to maximize power density regardless degradation mechanisms. Mostly, these operating conditions are defined by the manufacturer of the system and here are assumed based on Wen et al. [13] (T = 1073 K, i = 1.9 A/cm^2). The second strategy is based on DBO and system operates at the conditions which are derived from developed DBO framework. Techno-economic analysis is performed to compare these two strategies. Power generation and system lifetime profit are two indexes of techno-economic analysis. The system under study is the UPM-570 Uninterruptible Power Module manufactured by Bloom Energy. Its data sheet is presented in the Table 3.

In addition, the constant parameters utilized to obtain the simulation results are listed in the Table 4. It is assumed that SOFC stack will fail if the half of Nickel on the anode surface is degraded [39].

Based on optimization strategies, two optimization models are solved. The optimum decision variables are presented in the Table 5. It should be noted that both strategies are optimized. The base case strategy optimizes operating variables in order to maximizing initial power at a specific operating temperature, while DBO strategy optimizes operating variables based on system degradation to achieve maximum lifetime profit. Genetic algorithm method is used in proposed DBO framework to determine the optimum decision variables. Flow data of optimization procedure based on GA algorithm is presented in the Fig. 8. A random set of decision variables based on GA algorithm conditions are selected. These vectors are applied to the degradation and process models. The process and degradation models are a set of partial differential equations. An approximate solution is obtained at a discrete set of points at discrete times. The time interval is 1 h and all variables are determined hourly till system meets the failure constraint (half of nickel on the catalyst layer degrades). Afterward system power generation and efficiency through time is calculated and system profit terms (income, fuel cost and degradation cost) are derived. This procedure is done for all elements of decision variable vectors and according to that, the profit vector will be defined. Finally, the maximum value of profit defines the optimum decision variables element. This procedure is solved in MATLAB 2013a.

Table 3
System under study: UPM-570 data sheet [38].

Inputs	
Fuel	Natural gas, direct biogas
Input fuel pressure	15 psig
Output	
Nameplate power output (net AC)	160 kW/200 kV A
Base load output (net AC)	150 kW
Electrical connection	480 V @ 60 Hz, 3 or 4-wire 3 phase
Maximum Load Step	50 kW
Maximum Parallel Configuration	5 Units (750 kW) (600 kW with N + 1)
Standalone Operation Duration in Grid Outage	96 h (4 days)
Physical	
Weight	5000 lbs
Size	4′ 2″ × 8′ 7″ × 6′ 9″
Environment	
Standard temperature range	−20°–45 °C
Humidity	0%–100%
Seismic Vibration	UBC Seismic Zone 4
Location	Indoor/Outdoor
Noise @ rated power	<70 dBA @ 6 feet

Table 4
System constant parameters.

Parameter	Value	Unit	Reference
System operation time	15	year	–
Operation factor	0.91	–	–
Temperature range	973–1073	K	–
Current density range	0–4	A/cm^2	–
Electricity price	0.138	$/kW hr	[40]
Natural gas price	0.06	$/m^3	[41]
SOFC stack cost	2.25	$/kW	[42]

Table 5
Optimum operating variables based on two optimization strategies.

	Base case	DBO strategy
Temperature (K)	1073	1048
Current density (A/cm^2)	1.9	1.68

Power generation through system lifetime for two operating strategies is presented in the Fig. 9. As it can be seen, at the base case, system operates at higher power level, but degradation mechanisms are not controlled and performance deteriorates drastically. Moreover, uncontrolled degradation mechanisms, causes system failure after 11,900 operating hours. On the other hand, DBO strategy integrates degradation mechanism effects into the optimization procedure. This leads system to operate at lower initial power while power deterioration rate is much lower than base case and the replacement interval increases to 45,000 operating hours (last 3.78 times more).

To illustrate the effectiveness of degradation based optimization techno-economic indexes of two optimization strategies are compared. Power generation and lifetime profit are considered as two indexes, which are presented in the Table 6.

DBO results show while power generation decreases 19.4%, the system lifetime profit increases 10.45% in comparison with the base case (Table 6). Although power generation decreases, the fuel cost and degradation cost increases dramatically. It is because the DBO determines operating conditions and replacement intervals which lead system to operate at lower power level with lower performance deterioration. Lower level of power generation decreases power generation and fuel cost. Furthermore, lower performance deterioration increases replacement interval. Therefore system degradation cost (Maintenance/replacement cost) is much lower. Lower degradation cost overcome lower power generation income and these lead system to operate at higher profit through its lifetime.

Accumulated profit or lifetime profit is a parameter which can clearly illustrate system profitability over time. Fig. 10 depicts accumulated profit over time. It is clear that accumulated profit of DBO strategy is more than base case strategy over the whole period. These gap is increases during time, which is approximately 77,000 $ after 120,000 operating hours.

As mentioned before, the lifetime profit includes income, operating and asset degradation costs. The trends of accumulated values during system lifetime are presented in the Fig. 11. Although accumulated income of base case is higher than DBO strategy, the degradation cost is much higher and overcome the income level.

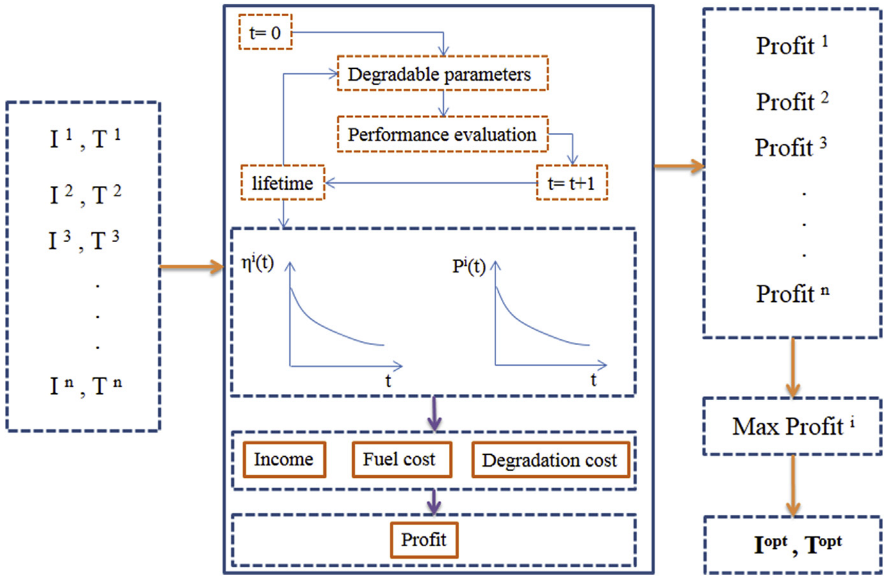

Fig. 8. Genetic algorithm solution approach of DBO model.

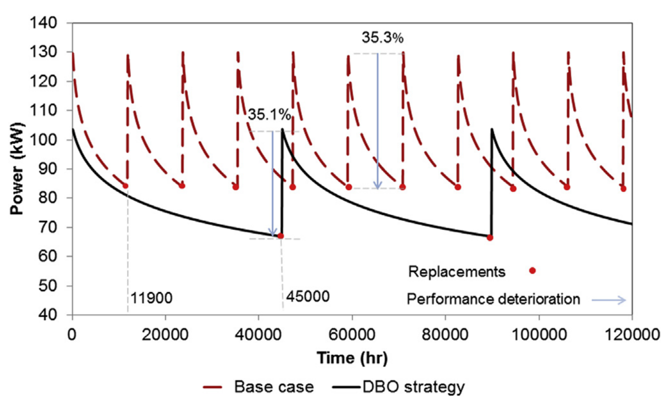

Fig. 9. Optimum power generation based on two operating optimization strategies over time.

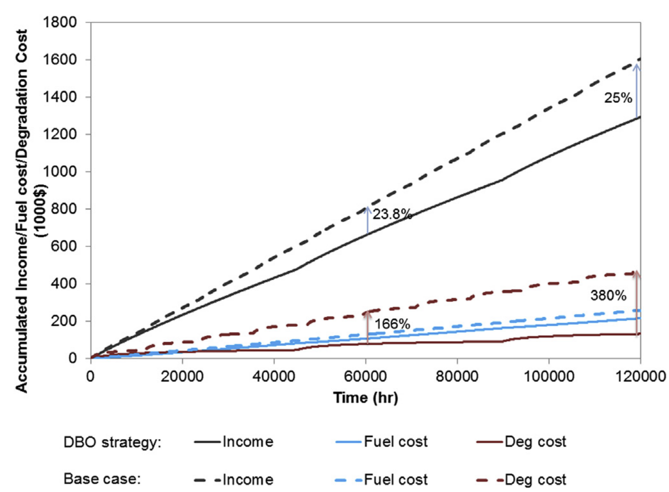

Fig. 10. Accumulated profit based on two operating optimization strategies over time.

Table 6
Techno-economic indexes of two optimization strategies.

	Base case	DBO strategy	Decrease/Increase percentage
Power generation (MW hr)	11,579	9321	−19.4%
Lifetime profit ($)	893,050	986,400	+10.45%

Therefore, the lifetime profit based on DBO strategy is improved in comparison with the base case strategy. This is due to the fact that DBO model considers degradation cost in its objective function. Therefore system operates at an operating strategy which maximize profit regarding degradation cost (correspond to replacement cost). In the most usual operation optimizations like base case, system operates at an operating strategy regardless degradation cost. Therefore, system has more degradation cost. This phenomenon is illustrated in Fig. 9 as well. Operating at base case, leads system to be replaced ten times during the operating lifetime. However, operating at optimized conditions reduces the replacement to two times and therefore system degradation (replacement) cost is about one fifth.

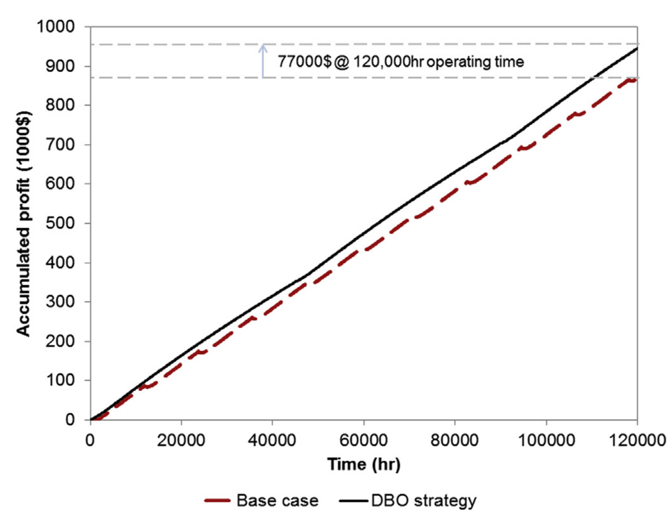

Fig. 11. Accumulated income, fuel and degradation cost based on two operating optimization.

Fig. 11 shows that the degradation cost is a crucial parameter which highly affects system lifetime profit. Degradation cost shows system cost because of aging at a given operation mode. In order to find out how the degradation cost term in objective function affects the outputs, a weighting coefficient w_a is defined in the objective function (Eq. (27)).

$$\max J[u(t), x(t), t_l] = \int_{t}^{t+t_l} (q(t) - c_o(t) - w_d \times c_d(t))d\tau \tag{27}$$

This sensitivity analysis clarifies the effect of system degradation cost on system optimum operating condition and replacement interval. The comparison is performed for 0, 0.5 and 1 degradation cost weighting factors.

There are many criteria which can be used as the performance index. Here, power generation through time is presented as an index to compare different optimization strategies. Based on Fig. 12, by increasing the weight of degradation cost, system operates at lower power value with higher replacement intervals. The reason is, when degradation cost weighting factor increases, system prefer to operate at conditions which minimizes the degradation mechanism rates. These operating conditions decrease the power level while the replacement interval is expanded.

The accumulated system profit is reported as an economical index in the Fig. 13. It is clear that degradation has significant effect on system economics. As it can be seen by increasing the degradation cost weighting factor in the objective function, system profit increases drastically. By considering degradation cost, system operates at conditions which lead to lower degradation cost through system lifetime. This results in higher lifetime profit.

The online profit is presented in Fig. 14. Online profit begins from point A and increases over time (point B). The reason is at the initial time the degradation cost (corresponding to degradation rate) is high enough to cover income. As time passes, the degradation rate slow down and as the result the online profit is improved till it reaches to maximum value at point B. afterward, system degradation rate is almost constant and income decreases because of degradation mechanisms. This fact causes online profit falling from point B to point C.

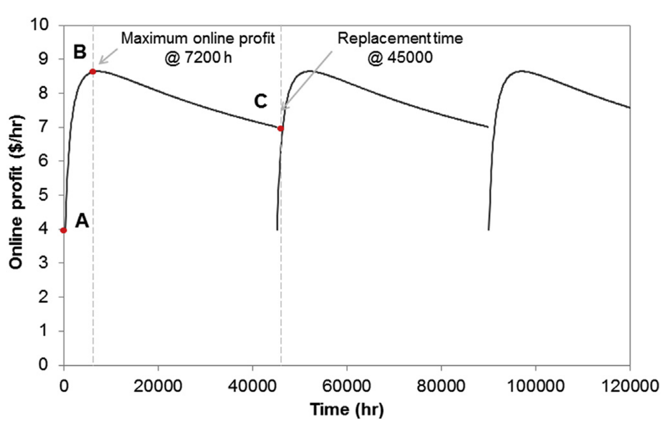

Fig. 12. Optimum power generation over time at three degradation cost weighting factor strategies over time.

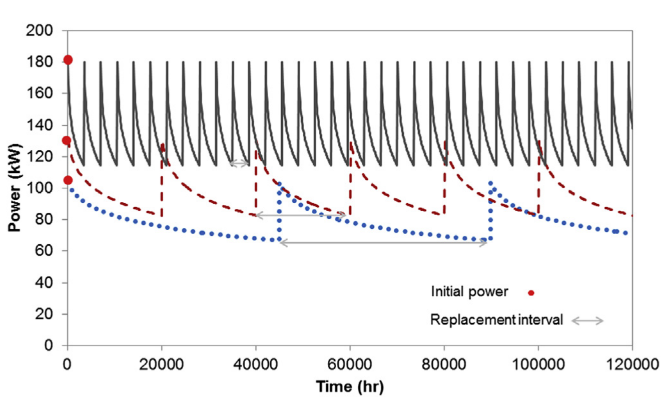

Fig. 13. Accumulated optimum profit over time at three degradation cost weighting factor.

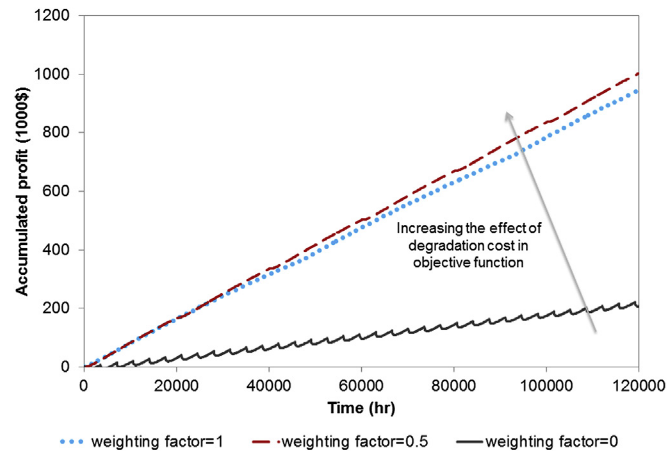

Fig. 14. Optimum online profit based on DBO strategy over time.

6. Conclusion

The use of optimization models are central components of profit maximization for today's energy systems. In this study, degradation based optimization (DBO) framework is developed. The objective of DBO in energy systems is to maximize profit through system operation lifetime. DBO outputs determine when to turn equipment on and present the optimum operating condition and replacement intervals. The new element in this approach is the explicit handling of degradation models and their inclusion in the optimization routine. The degradation models provide a direct relationship between plant operating conditions and plant ageing.

The DBO framework is applied to a SOFC system and optimum operating conditions and replacement intervals are derived. The main conclusions of the present study are as follows:

- The validation process demonstrates the suitably of the modeling tool to represent the performance deterioration of anode supported SOFCs by successfully matching experimental data for a fuel cell operating at various current densities.
- Using DBO framework, lifetime profit through 120,000 h of operation of SOFC system is 10.45% higher in comparison with base case which is equal to 77,000 $.
- Using DBO framework, degradation cost decreases to a quarter. However the income of system decreases about 25%. In this case, the overall profit through lifetime is improved.
- By increasing the effect of degradation cost using weighting factors in the DBO objective function, system replacement

intervals are increased. This leads to an improvement in system lifetime profit.

In this study, the validation and demonstration of the DBO framework laid the framework for considering the degradation and long-term performance of SOFC. However, the DBO framework model can now be expanded to look at degradation and performance deterioration of any other energy systems.

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